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Unobtrusive Tremor Detection and Measurement via Human-Machine Interaction

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Abstract

Elderly people possess enhanced working experience during their living. Therefore it is a big value loss for companies, when such individuals get into retirement. Through the development of a novel workspace, which allows elderly people to maintain work- active in a decentralized manner, e.g. from home, this limitation, caused by the demographic change, can be overcome. Additionally most people in advancing age usually suffer from different diseases. By using recent computer-user interfaces like motion sensors devices or smart glasses, it is possible to measure physiological readings unobtrusively while gesture or intuitively controlling a personal computer or system. The authors propose the implementation of a tremor detection system embedded in this decentralized workspace, using the Leap Motion controller as well as the Vuzix Smart Glasses M100.

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Keywords: tremor; fast fourier transformation; smart glasses; parkinson; human-machine-interaction, leap motion controller

1. Implementation of Augmented Reality and Gesture detection in a decentralized Workspace

Tremor is a symptom caused by several diseases, which starts in medium or advancing age, and affects mainly the respected target group users of the proposed decentralized workspace. Parkinson is one well known disease, and belongs in Europe to one of the most occurring neurological diseases, with a prevalence rate of 0.1 % to 0.2 % of the population [1]. In [1] it is also mentioned that for people older than 65 years the prevalence increase to 1.8 %. Essential

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Tremor is occurring up to 20 times more often than the tremor in Parkinson, and tends to additionally affect the user head [2]. The prevalence of Essential tremor is 0.4 % up to 3.9 % [3], and therefore comparable with epilepsy, migraine, and stroke or lumbosacral pain syndrome [2]. Up to 5 % of the population, which is older than 65 years is suffering from essential tremor [2].

In the past, several studies investigated possibilities to measure tremor [4, 5] in order to support physicians in the diagnostics, e.g. by distinguishing between Parkinson, Essential Tremor or further diseases which cause similar tremor patterns (e.g. cerebellar, dystonic, orthostatic, holmes, psychogenic tremor [2]). This can be done, e.g. by frequency analyses of the appropriate body areas. In [6] an unobtrusive measurement by a wrist wearable device was developed for detecting Parkinson's tremor, including bradykinesia. Furthermore, in [7] up to 23 different indicators were investigated in order to identify differences in age groups from 70 up to 100 years. The results show the potential of the "young aged". Elderly people, especially between 50 and 70, have still a high work performance and enhanced experience, which is deemed irreversibly lost for the society and industry, once they move into retirement scheme. Furthermore, according to [8, 9] mental activity is protecting for accelerated senilism. Additionally, due to the demographic change, the "generation contract" probably will not work in that way as it is, at moment. Therefore a novel workspace has been proposed and developed, which enables elderly people to work decentralized e.g. from at home, supported by AAL technologies [10].

Until now, to the best of the authors knowledge, there is no implementation using the Leap Motion controller sensor and or the Vuzix M100 Smart Glasses to detect tremor unobtrusively, while using these devices as a computer-user interface. As the detection of both devices is working unobtrusive at the same time, diagnostics for Parkinson's disease and essential tremor are enabled.

2. Implemented service at the proposed Workspace

2.1. Leap Motion controller as a Robotic Arm Interface

A novel approach for controlling a robotic arm, as a supporting system in a workspace, using the Leap Motion controller was developed [11]. The idea was to implement a new gesture-based human-machine interaction scheme, using the Leap Motion controller and the 6-DOF robotic arm, Jaco. When dealing with gesture-based user interfaces, the accuracy of the sensor is greatly considered a challenging task [12, 13, 14]. The Leap Motion controller (depicted in Figure 1 (a)) comprises an optical sensor based on three infrared emitters and two infrared cameras. The controller is considered a breakthrough device in the field of hand gesture controlled Human-Machine-Interfaces, as it introduces a novel gesture and position tracking system with sub-millimeter accuracy, and high throughput rate of up to 300 samples per second [15]. The user hand movements are accurately tracked by the Leap controller. The proposed algorithm translates this information into useful commands in order to control the robotic arm Jaco in a real-time manner. The system can detect and process the user's palm displacement and orientation according to the user hand tremor patterns, adapting in run-time the output data sent to the robotic arm, in order to filter out unwanted oscillation and to enable smooth operation to allow for grab, pick and place tasks. More details of the developed interface can be found in [11].

2.2. Incorporation of AR Smart Glasses in the Workspace

The Vuzix M100 is a commercially available pair of smart glasses that runs on Android OS. It has an onboard OMAP4460 processor rated at 1.2 GHz clock speed, 4 GB RAM and 4 GB flash memory. The device's 3-axes gyroscope, 3-axes accelerometer, ear speaker and camera are utilized by the proposed implementation. The 5 Mpixel spatial resolution front camera can capture full HD (1080p) images and videos [16]. An Augmented Reality (AR) based application was developed to assist elderly in operating the workspace. The augmented text instructions assist the user upon identifying the different workspace systems and their corresponding features and uses. Additionally, voice guided instructions are fed via the inbuilt earphone of the smart glasses to the user, regarding the process to successfully control each system. For detecting the different workspace systems, the Metaio SDK has been used [17]. For the voice guidance the Text-To-Speech class from Android API has been used [18]. As the Vuzix smart glasses offer accelerometer and gyroscope sensor data, the potential of a gesture analysis, e.g. for head tremor, as investigated in [12] for Parkinson disease, is enabled by implementing the tremor detection algorithm, which also has been used for the Leap Motion controller.

3. Hand Tremor detection using the Leap Motion controller

The enhanced precision of the Leap Motion controller, is considered a disadvantage for the robotic arm manipulation on the one hand, due to the fact that any hand tremor patterns are directly translated to unwanted oscillation on the robotic arm side e.g. when operated by a patient with Parkinson's disease; this problem can be minimized via a pre-process calibration step. On the other hand, the sub-millimeter accuracy of the controller could be seen as an opportunity for detecting symptoms related to hand tremor, which can indicate an abnormal disorder.

3.1. Implementation of monitoring and detection of Tremor using the Leap Motion controller

Since the Leap Motion controller can supply information about the different user palm position and orientation (see Fig. 1 (b)), the measurement of the roll data could be enabled, which is mostly dominant in hand tremor.

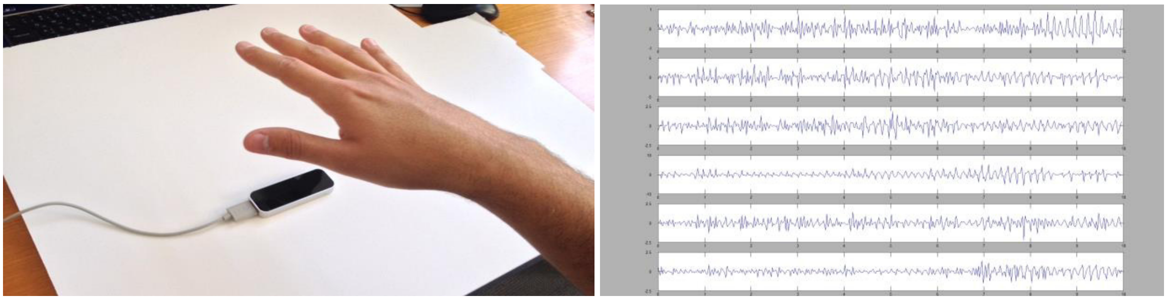

Fig. 1. (a) Leap Motion controller user palm position and orientation tracking;
(b) data streams (x, y, z, roll, pitch, yaw) measured by the Leap Motion controller.

The acquired data (x, y, z position, and roll, pitch, yaw orientation of the user palm) by the Leap Motion controller are fed into the proposed algorithm to be recorded for a defined period of time (*t*), at a certain sampling frequency $F_{sampling}$ predetermined according to the number of frames received from the sensor during the time (*t*). According to the time window and the amount of frames $N_{samples}$ which has been recorded, the sample frequency $F_{sampling}$ can be calculated for this specific time window using "Eq. (1)":

$$F_{sampling} = \frac{N_{samples}}{t} \quad (1)$$

The approximate derivative is calculated twice in order to obtain the acceleration i.e. the rate of change of velocity. The acceleration arrays are then passed to the Fast Fourier Transform (FFT) algorithm, which transforms the data from the time domain to the frequency domain "Eq. (2)".

$$\bar{x} = \left| F\left(\frac{\Delta^2 x}{\Delta t^2}\right) \right| \quad (2)$$

Where $\bar{x}$ represents the Fourier transformation, x the position data of the user palm in cm (measured by the Leap Motion controller), and t the time in seconds (a time window of 10 seconds was used). The first approximate derivative v of each input array x is obtained by applying "Eq. (3)".

$$
\begin{gathered}
x = [x_0\ x_1\ x_2\ x_3 \dots x_n] \\
v = diff(x), \quad a = diff(v) \\
v_i = \Delta x_i = x_{i+1} - x_i \\
v = [(x_1 - x_0)(x_2 - x_1)(x_3 - x_2)\dots(x_n - x_{n-1})]
\end{gathered} \tag{3}
$$

By applying the Aitken's delta-squared process, the second approximate derivative or acceleration a could be obtained using "Eq. (4)".

$$
\begin{gathered}
a_i = \Delta v_i = \Delta^2 x_i = v_{i+1} - v_i = x_i + x_{i+2} - 2x_{i+1} \\
a = [(v_1 - v_0)(v_2 - v_1)(v_3 - v_2)\dots(v_n - v_{n-1})]
\end{gathered} \tag{4}
$$

The formulas used for doing the FFT are the ones introduced by Danielson and Lanczos in 1942 [19]. To test the FFT process, a known input (i.e. a sinus function) was first used as an input. A sinus function was modeled with a frequency of 1 Hz, sampling frequency of 20 Hz, and time of 10 seconds (visible in Fig. 2 (a)). The FFT analysis (shown in Fig. 2 (b)) revealed a sharp peak at a frequency of 1 Hz, which proves the robustness of the FFT implemented algorithm.

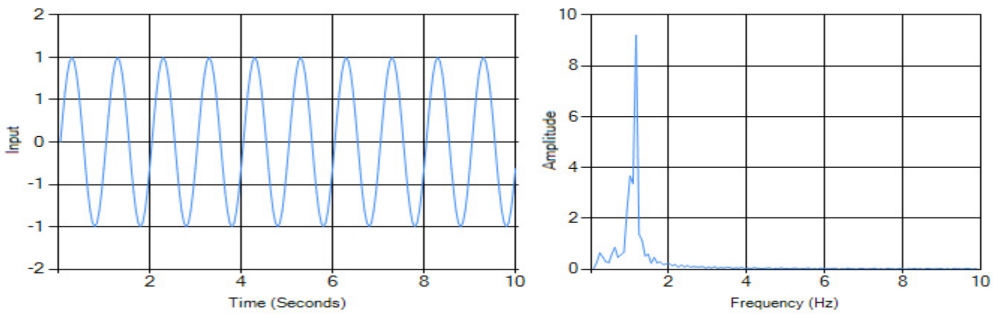

Fig. 2. (a) Input signal for testing the algorithm by a sinus function; (b) FFT result of the input sinus function.

Each tremor related disease is known to exist at a certain range of amplitude and frequency [2], e.g. Parkinson's disease ranges between 5 and 12 Hz and essential tremor between 4 and 8 Hz, therefore the analysis results could assist towards the detection of such symptoms. The resulting plots of the FFT, are then analyzed in order to decide whether the user really suffers from any tremor related disorder or not. The factors that affect this analysis are the dominant frequency (the peak of the graph in Fig. 2 (b)), and the amplitude at this dominant frequency.

To smoothen the signal before the FFT step a window function is used. Different window functions were tested (e.g. Gaussian window, Hamming window, and Kaiser Window [20]), in order to find the most suitable one. The Gaussian window provided the best results, and was therefore applied to the analysis procedure, by "Eq. (5)".

$$
w(n) = e^{-\frac{1}{2}\left(\frac{n-(M-1)/2}{\sigma(M-1)/2}\right)^2} \tag{5}
$$

Here, M represents the length of the array, which has to be the same length of the array of the Fourier transformed, and n is the corresponding index of the array. Responsible for setting up the Narrowness of the window function, the value of σ was set to 0.3.

Fig. 3 represents the steps involved during the proposed analysis cycle. This procedure is considered an early stage detection of symptoms, it does not ensure whether this person has Parkinson's or other disease or not. This is due to the fact that the analysis considers the tremor part only, neglecting for the time being other symptoms such as rigidity, bradykinesia, and postural instability etc. Such an approach though enables the importance of having an early stage detection system that could warn the user at an early phase of the disease, which might make the treatment much more effective.

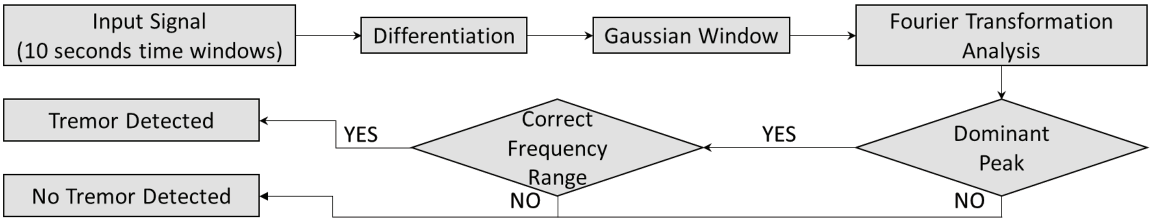

Fig. 3. Proposed tremor detection process.

3.2. Results

In order to prove the proposed hand tremor detection approach, some graphs are depicted in this section. The graphs present the analysis performed on the user palm orientation, specifically the roll angle, which is most dominant in tremor patterns. The first pair in Fig. 4 (a) shows the scenario when no tremor was introduced to the Leap Motion controller, and the second pair (Fig. 4 (b)) shows the result when a tremor pattern was introduced. In each pair of plots, the first shows the hand roll input signal in degrees (directly received from the Leap Motion controller and represents the user palm position), plotted against time (i.e. approx. 10 seconds). The second plot illustrates the FFT of the input signal.

As it is clear on the first plot of the first pair, see Fig. 4 (a) (left), the user hand roll value was almost constant with only small fluctuations occurring throughout the 10 seconds window. This was clearly reflected on the FFT Analysis, visible in Fig. 4 (a) (right). The amplitude values are very low ranging between 0 and 3.1, we can also conclude the nonappearance of any dominant frequency.

Fig. 4 (b) shows the same analysis performed when a hand tremor pattern was introduced. The left plot shows fluctuations in the user hand roll input signal, ranging between -10 and -40. The Fast Fourier analysis in the right plot (Fig. 4 (b)) confirmed the existence of a dominant frequency centered at 7 Hz. It is also clear on the Y-axis of the plot that the amplitude range widely increased reaching a peak of 520 at the dominant frequency, compared to the same FFT analysis on the tremor absence case, which is superimposed for comparison purposes in Fig. 4 (b) with the red line.

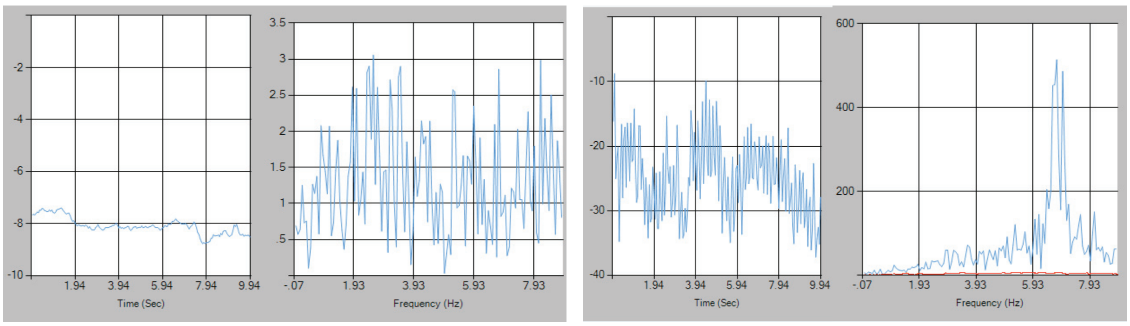

Fig. 4. (a) Left is the input signal of the Hand Roll (in degrees) without tremor, on the right the FFT result (zoomed) of such a tremor free movement is visible; (b) left is shown the input signal of hand roll with a tremor, on the right the FFT result, which marks the dominating frequency of 7 Hz.

4. Head Tremor detection using Smart Glasses

4.1. Concept Description

Fig. 5 (a) presents the position and orientation of accelerometer and gyroscope sensors in the smart glasses, as well as the application (Fig. 5 (b)) to initiate the implemented tremor detection algorithm of the Vuzix M100 when worn.

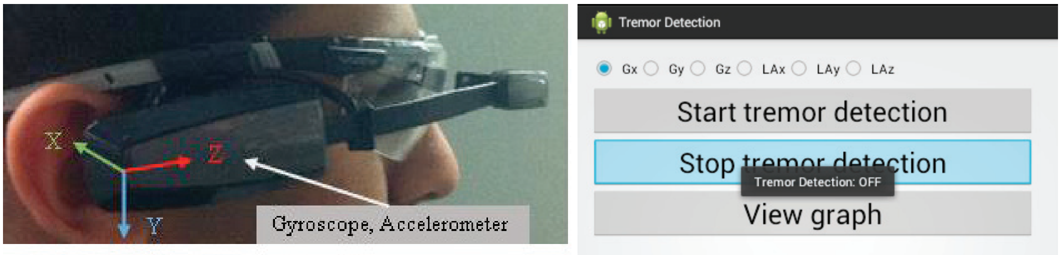

Fig. 5. (a) Position of sensors and coordinate system of the Vuzix M100; (b) GUI for initiating the tremor detection in the Vuzix M100.

The algorithm explained by Eq. 1-5 and Fig. 6 is running in real-time while the application is used. This enables the possibility of the detection of head tremor while the workspace is being used. The sensor readings can be acquired at a maximum rate of 200 samples per second. Such a throughput was proven more than sufficient to detect tremor in order to distinguish between essential tremor and other diseases, e.g. Parkinson. To apply the algorithm to the glasses following changes were made in "Eq. 2". As the gyroscope sensor measures the rate of rotation around each physical axis of the device in rad/s [21], the readings are only once differentiated. Therefore "Eq. 2" changes to:

$$\bar{v} = \left| F(\frac{\Delta v}{\Delta t}) \right| \qquad (6)$$

Here, v is gyroscope's readings in rad/s, and $\bar{v}$ is the Fourier transformed of the differentiated readings. For the differentiation "Eq. (3)" is used.

Linear acceleration measures the acceleration force applied to all three physical axes of the device, including gravity, in m/s² [21], therefore there is no differentiation needed "Eq. (2)" can be simplified to "Eq. (6)" as follows:

$$\bar{a} = |F(a)| \qquad (7)$$

Here, a stands for linear acceleration in m/s² and $\bar{a}$ for the Fourier transformed value.

4.2. Implementation of monitoring and detection of Tremor using the Vuzix M100

As both, the accelerometer and the gyroscope have 3 axes, there are 6 measured data values. The tremor detection algorithm is applied as a "service" in the application. This enables the algorithm to run in the background even when the application is minimized. In an Android application, a service is a component that can perform long running operations in the background and does not provide a user interface [22].When the application starts, the readings of the gyroscope x axis are recorded, i.e. the device rate of rotation relative to its x axis. In the tremor detection section of the application (Fig. 5 (b)) the user can change the axis depending on the requirement.

As soon as the user changes the required axis, the service will restart, and only the required sensor will be registered. The detection for the selected axis starts immediately. The user can stop or restart the detection process again from the same GUI part. When the service is started or stopped, the user is notified via a small popup message. Until the application is terminated the service keeps running and the user preferences are saved. In Fig. 6 the proposed algorithm flowchart can be seen. At an interval of 3 seconds gathered sensor readings are processed.

Processing time varies between 1-10 milliseconds. As the frequency of 200 samples per second is not necessary, a software timer is set to normalize the input data process on every 7 msec, which results in an average recording frequency of 140 Hz.

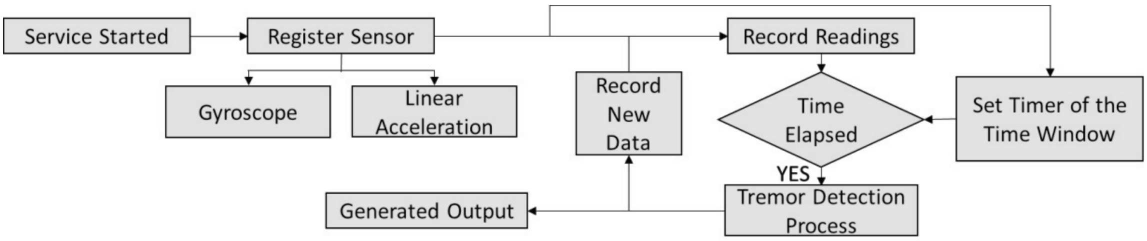

Fig. 6. Proposed pre-processing to enable the compatibility of tremor detection process between the Leap Motion controller and the Vuzix M100 smart glasses

4.3. Results

The algorithm was tested on a sinus wave input which has a time window of 1 second and a frequency of 10 Hz, similar as it was done with the hand tremor detection. Fig. 7 depicts the transformed output of the readings of the actual gyroscope's x axis values. Fig. 7 (a) shows the result when the user head is relatively steady, and Fig. 7 (b) presents a clear detected peak, when a head tremor of approximately 8 Hz was imitated.

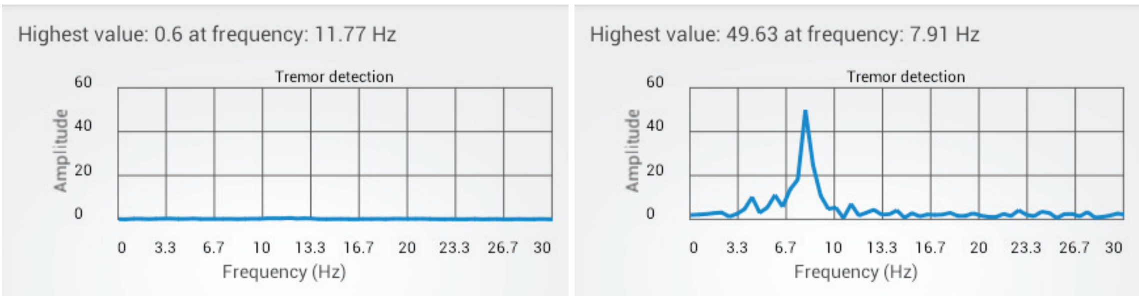

Fig. 7. (a) Gyroscope's x axis: Steady head; (b) Gyroscope's x axis: Imitated tremor pattern detection.

5. Conclusion and Discussion

A novel implementation in order to monitor and detect hand tremor while gesture controlling service robots by the Leap Motion controller, and head tremor while using an AR application running on the Vuzix M100 smart glasses, has been proposed. Such an approach enables the unobtrusive measuring and detection of tremor. The detected results and measured data can be efficiently used for diagnostic by physicians, etc. Moreover, a personal health alert system can be developed according to this proposed approach.

The authors showed the principal functionality by implementing the tremor detection algorithm into a decentralized workspace for elderly, which enables them to remain active even after retirement. Especially for this particular target group, the implementation of unobtrusive measurements is of highly importance, since they are prone to various diseases and disorders. The uncomforting use of worn or handheld measurement devices is reduced by this approach to a minimum, as the sensing is performed unobtrusively in the background, while the smart glasses and the Leap Motion controller are being used.

In a further study the authors will focus on testing the implemented system on actual tremor patients, by a ground truth clinical study, or at least the proposed tremor detection implementation can be of great importance for a business market level for healthcare and remote unobtrusive monitoring applications and products. Of course such a study should not only be limited to the tremor validation aspect, but also to focus on the usability and intuitiveness of the proposed system (guidance by AR as well as gesture control). Therefore, in future also various spatial resolution configurations regarding the smart glasses will be investigated, or even how efficient the operation by gesture recognition and augmented reality is. The authors believe that professional clinical studies using the proposed tremor detection method could enable the implementation of such devices into the AAL research areas.

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